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PARTICLE SWARM OPTIMIZATION (PSO)-BASED DISTRIBUTED POWER CONTROL ALGORITHM FOR WIRELESS RADIO SYSTEMS

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Abstract
Power control in wireless radio system has been explored since the early 1990's. Many researchers have developed algorithms to address problem of power control. Most of the algorithms in recent consider either the problem of minimizing the sum of transmitted power under quality of service (QoS) constraints given in terms of minimum carrier-to-interference ratio (CIR) in a static channel or the problem of mitigating fast fading in a single dynamic link. In this paper, a new approach to the power control was develop by treating the QoS requirement as another objective for the power control and the resulting constrained multi-objective-objective optimization problem is solved by means of particle swarm optimization (PSO).The convergence properties of the proposed algorithm are studied both theoretically and with numerical simulations. Noisy, dynamical environment is assumed in the simulations. The algorithm was modified to take throughput into consideration. Simulations demonstrated that the proposed power control algorithms converged faster than the conventional power control algorithms. Also, the average transmitted power was less than the average transmitted power using the conventional methods with comparable Quality of Service (QoS).

Keywords: Mobile Station, Base Station, Power Control, Throughput, Particle Swarm Optimization (PSO).

1. Introduction

Power control is essential in interference-limited capacity communication systems such as the direct-sequence code-division multiple access (DS-CDMA). The power control regulates transmitted powers of the users to be as close to optimum as possible. The optimum transmission power is the minimum power needed to achieve some target quality of service (QoS) level to users, which is usually expressed in terms of carrier-to-interference ratio (CIR). The power control mitigates the well-known near-far problem in DS-CDMA systems, which results in enhancing the system capacity and performance (Foschiniand Miljanic, 1993; Pao and Chen, 2014). Moreover, power control prolongs the operation time of the battery of mobile terminals and reduces the interference to other cross-channel communication systems by minimizing the transmitted powers. For this and other reasons, the power control problem has been receiving a lot of attention in the wireless communication literature. Although the power control problem is well understood, there still remain many related problems that are under active research such as speeding up the convergence of power control algorithms, determining the optimum implementation of the distributed power control (DPC), designing DPC without snapshot assumption that is fixed channel gains, and joining the power control with other resource control methods such as rate control and spatial processing.

It can be shown that the minimum transmitted power vector, which is required to achieve the target CIR to users, is the solution of a system of linear equations. Direct solution of this system is called centralized power control, and it requires full knowledge of the channel gains between all active transmitters and receivers. This required knowledge makes the centralized power control impractical method. There are many iterative algorithms to solve the power control problem in distributed fashion. The commonly used methodology in the literature of DPC is the so-called snapshot analysis. The system parameters such as gains and noise levels of users are assumed to be fixed or slowly changing compared to the rate at which power updates can be performed. This assumption is required to allow the DPC to converge to the solution of the centralized power control algorithm. In practice, however, the link gains of mobile channels have fast and random fluctuations that occur in the same time scale as power can be updated. These characteristics of mobile channels reduce the significance of the snapshot convergence property of the power control algorithms. The works of Grandhi *et al*. (1994) and Timand Lin (1996) does not assume the snapshot analysis, but the resultant power control algorithm is relatively difficult to implement in a very limited processing power handset.

The QoS constraint usually is not sharp; rather, it has some margin in which the QoS remains acceptable. To be more specific, the QoS is accepted if it falls within a set that is lower limited by the minimum accepted QoS and upper limited by the supremum QoS (Tadrous *et al.* 2011). The minimum accepted QoS is the lowest acceptable connection quality, any level below that is unacceptable. The supremum QoS is defined as the upper bound for the QoS. The preferred power control is that one that can achieve an accepted QoS level (i.e., a level that is between minimum and supremum QoS levels) very fast at low power consumption. This proposed power control algorithm fast achieves an accepted QoS level at very low power consumption. The power control algorithm is based on a snapshot assumption that the channel parameters as well as the mobile location are to be fixed for static scenario. This assumption is not valid for mobile communication systems due to their dynamic behavior. Actually, studying the convergence behavior and the performance of the distributed power control algorithms based on the snapshot assumption does not give a lot of information about their behavior in real systems. The reason is that for dynamical systems the channel parameters, "simply the link gains", are changing fast. In some cases, the channel parameters become uncorrelated after a fraction of a millisecond (Elmusrati et al., 2007; El-Sherif and Mohammed, 2014). In the case of a dynamical channel, a good power control algorithm is an algorithm, which can track the fast, dynamical changes of the channel. In the formulation, the optimum distributed power control algorithm is presented, which can track fast variations in the channel, while optimizing certain parameters. The objective is to keep the transmitted power as close to the minimum power as possible.In this paper, it will focus on the uplink power control case. It assumes that the CIR of each user can be estimated accurately and is available for the power controller. A method to estimate the CIR at the handset is proposed by Yates (1995), and Manish and Chandra (2016). This estimation of CIR is based only on 1-bit feedback channel. The paper is organised as follows: Methodology, derivation of multi-objective distributed power control algorithm, the numerical results, and finally, discussion and conclusion.

2. Materials and methods

2.1 Multi-Objective Distributed Power Control Algorithm

The proposed algorithm in this paper aims to achieve two objectives by applying the particle swarm optimization method. The first objective is to minimize the transmitted power, and the second objective is to achieve an accepted QoS level in terms of carrier-to-interference ratio.

2.1.1 Transmitted Power and Carrier to Interference Ratio

Mathematically the power control problem is formulated as follows: To obtain the power control vector P, which minimizing the function as in (Yates, 1995; Gnatcatcher, 1964) can written as follows.

$$J(\mathrm{P}) = 1^T \mathrm{P} = \sum_{\mathrm{i}=1}^{\mathrm{Q}} \mathrm{p_i} \qquad (1)$$

Subject to

$$\Gamma_{ki} = \frac{P_i G_{ki}}{\sum_{\substack{j=1 \\ j\neq i}}^{Q} P_i G_{ki} + N_i} \geq \Gamma^*, i = 1, .., Q, k = 1, \dots, M \qquad (2)$$

and

$$\mathrm{P_{min}} \leq P_i \leq P_{max}, \forall \mathrm{i} = 1, \dots, \mathrm{Q}, \qquad (3)$$

The transmitted power is given as

$$\mathrm{P}_i(t) = \sum_{\mathrm{k}=1}^{\mathrm{n}} \mathrm{w_i}(k)\mathrm{P}_i\,(\mathrm{t}-\mathrm{k}) = \mathrm{w_i^T X_i(t)} \qquad (4)$$

Where $w_i^T = [w_i(1) \dots \mathrm{w_i(n)}]$, $\mathrm{X_i(t)} = [\mathrm{P_t(t-1)} \dots \mathrm{P_i(t-n)}]^{\mathrm{T}}$.
It can be observe that $X_i(t)$ contains known, measured values of transmitted power.

The power control algorithm will be derived, while solving the minimization problem of Eqn. (3). The power *Pi(t)* is described by an autoregressive model as shown in Figure 1 (Zander, 1992).

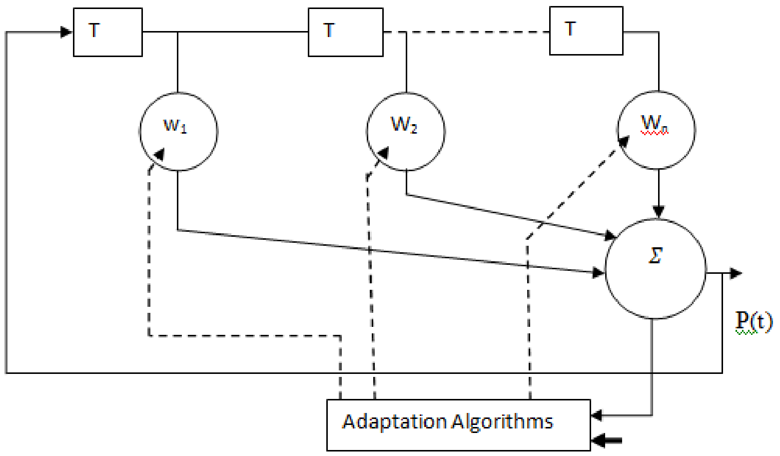


Figure 1: Autoregressive model of power control

The multi-objective problem in this case would be to minimize

$$J(P) = \begin{pmatrix} J_1(P_i) \\ J_2(P_i) \end{pmatrix} \qquad (5)$$

with respect to P_i subject to the following constraints.

$$\tilde{J}(P_i) = \sum_{i=1}^{2} (w_1 J_1(P_i) + w_2 J_2(P_i)), i = 1, \dots, Q. \qquad (6)$$

Here the weights $0 \leq w_1 \leq 1, w_2 = 1 - w_1$.
Where: J_1 and J_2 are defined as follows;

$$J_1(P_i) = (P_i(t) - P_{min})^2, i = 1, \dots, Q$$
$$J_2(P_i) = J_2(\Gamma_i(P_i)) = (\Gamma_i(t) - \Gamma^{tg})^2, i = 1, \dots, Q$$

The time dependence is taken into account by considering a time horizon t = 1,…, N together with an adaptation factor. The power control problem then becomes:

$$J(P) = [\sum_{i=1}^{Q} \sum_{t=1}^{N} \gamma^{N-t} e_i^2(t)], t = 1, \dots, N \qquad (7)$$

To find the minimum of the objective function in Eqn. (7) with respect to the power vector P, the error $e_i(t)$ was defined as:

$$e_i(t) = \lambda_1(P_i(t) - P_{\min}) + \lambda_2(\Gamma_i(t) - \Gamma^{tg}) \qquad (8)$$

where: $0 \leq \lambda_1 \leq 1, \lambda_2 = 1 - \lambda_1$, and γ is an adaptation factor. Γ^{tg} is the target CIR, P_{min} was the minimum transmitted power of the mobile station, and P = [P_1……..P_Q].
The main idea of the function in Eqn. (4) is to keep the transmitted power Pi(t) as close as possible to P_{min} and, at the same time, to keep the CIR, Γi(t) as close as possible to the target CIR, Γ^{tg} . Eqn. (4) was substituted into Eqns.(8) and (2), then the error $e_i(t)$ became:

$$e_i(t) = \lambda_1(W_i^T X_i(t) - \mathrm{P_{min}}) + \lambda_2 \left(\frac{G_{ii}(t) W_i^T X_i(t)}{I_i(t)} - \Gamma^{tg} \right). \qquad (9)$$

By denoting

$$\alpha_t = \left[\lambda_1 + \lambda_2 \frac{G_{ii}(t)}{I_i(t)}\right] \tag{10}$$

and using it in Eqn. (8), $\boldsymbol{e_i(t)}$ became

$$e_i(t) = \alpha_t \mathrm{w}_i^T X_i(t) - \lambda_1 \mathrm{P_{min}} - \lambda_2 \Gamma^{\mathrm{tg}}. \tag{11}$$

From Eqns. (7) and (11), a necessary condition for the minimum transmitted power was found to be:

$$2\sum_{t=1}^{N} \gamma^{N-t}\, e_i(t) \frac{\partial e_i(t)}{\partial \mathrm{w}} = 0 \tag{12}$$

From Eqn. (10),

$$\frac{\partial e_i(t)}{\partial \mathrm{w}} = \alpha_t X_i^T(t) \tag{13}$$

Substituting the function in Eqns. (10) and (9) into (11) yielded Eqn. (14).

$$\sum_{t=1}^{N} \gamma^{N-t} e_i\,(t) \frac{\partial e_i(t)}{\partial \mathrm{w}} = \sum_{t=1}^{N} \gamma^{N-t} (\alpha_t\, \mathrm{w}_i^T X_i(t) - \lambda_1 \mathrm{P_{min}} - \lambda_2 \Gamma^{tg}) \alpha_t X_i^T(t) = 0 \tag{14}$$

The minimization of the function in Eqn. (14) with respect to Piis was then transformed into minimizing Eqn. (14) with respect to parameter vector w, for the minimization of transmitted power and the carrier to interference ratio (multi-objective).

2.1.2. Transmitted Power and Throughput of the power control cellular system.

In this procedure, the algorithm was based on the maximization of the throughput in the distributed power control cellular system. The throughput of user *i* was approximated when M-QAM modulation as used by (Elmusrati et al., 2007; and Nie et al., 2016) as in Eqn. (15)

$$\mathrm{T_i} = \Theta + \log_2 \Gamma_i \tag{15}$$

where: T_i is the throughput of user i, Θ is a constant, and Γ_i is the carrier to interference ratio of user I as in Eqn 16.

$$T = \sum_{i=1}^{Q} T_i = Q\Theta + \log_2(\prod_{i=1}^{Q} \Gamma_i) \tag{16}$$

where: Q is the number of users.

If the link gains G_{ij} of the users is given, then, the power vector P= $[P_1, P_2,...,P_Q]'$ will maximizes the throughput. Since the first term in Eqn. (15) is constant and the logarithmic function is an increasing function, then maximizing the multiplicative term ($\prod_{i=1}^{Q} \Gamma_i$) will lead to maximizing the throughput Tas in Eqns 18.

␣ = ◥$P \mid P_{min} \leq P_i \leq P_{max},\ i = 1, . . ., Q\}$ (17)

$$\underset{\mathrm{P}}{\mathrm{Max}} \{\mathrm{O(P)}\} \quad \mathrm{s.t.} \quad \mathrm{P} \in \Omega \tag{18}$$

Where

$$\mathrm{O(P)} = \lambda_1 \prod_{\mathrm{i=1}}^{\mathrm{Q}} \Gamma_{\mathrm{i}}\,(\mathrm{P}) - \lambda_2 1'\mathrm{P} \tag{19}$$

Eqn. (19) is the objective function, 1 = [1, 1, ..., 1]$'$, and the tradeoff factors real numbers,

$$0 < \lambda_1 < 1, and\ \lambda_2 = 1 - \lambda_1.$$

The necessary conditions for solving problem Eqn. (18) are:

$$\nabla \mathrm{O(P)} = 0, \tag{20}$$

Where $\nabla O(P) = [\frac{\partial O}{\partial P_1}, \frac{\partial O}{\partial P_2}, \dots, \partial OP_Q]'$ is the gradient of O. Substituting the CIR Eqn. (2) into (19) led to Eqn. (21).

$$O\big(P(t)\big) = \lambda_1 \prod_{i=1}^{Q} \frac{P_i(t)G_{ii}}{\sum_{\substack{j=1 \\ j\neq 1}}^{Q} P_i(t)G_{ii} + n} - \lambda_2 \sum_{i=1}^{Q} P_i(t) \qquad (21)$$

Since the obtained equations are nonlinear, it will be very complicated to get an analytical solution, the power vector P which satisfies equation (20) must be obtained. An iterative solution for k = 1,..., Q was formulated (the iteration argument, t was dropped for simplicity)

$$\frac{\partial O}{\partial P_k} = \lambda_1 \frac{(G_{kk}\prod_{i=1}^{Q} G_{ii}P_i)\prod_{i=1}^{Q}(\sum_{j\neq 1}^{Q} G_{ij}P_j + n) - (\prod_{i=1}^{Q} G_{ii}P_i)(\sum_{r\neq k}^{Q} G_{rk}\prod_{i\neq r}^{Q}(\sum_{j\neq i}^{Q} G_{ij}P_j + n))}{(\prod_{i=1}^{Q}(\sum_{j\neq i}^{Q} G_{ij}P_j + n))^2} - \lambda_2 = 0 \qquad (22)$$

Simplify equation above led to Eqn. (23)

$$\lambda_1 \frac{\left(G_{kk}\prod_{i\neq k}^{Q} G_{ii}P_i\right) - (\prod_{i=1}^{Q} G_{ii}P_i)\sum_{r\neq k}^{Q} \frac{G_{rk}}{(\sum_{j\neq r}^{Q} G_{rj}P_j + n)}}{\prod_{i=1}^{Q}(\sum_{j\neq i}^{Q} G_{ij}P_j + n)} - \lambda_2 = 0 \qquad (23)$$

which was written as:

$$\lambda_1 G_{kk}\prod_{i\neq k}^{Q} G_{ii}P_i - \lambda_1(\prod_{i=1}^{Q} G_{ii}P_i)\sum_{R\neq K}^{Q} \frac{G_{rk}}{(\sum_{j\neq r}^{Q} G_{rj}P_j + n)} = \lambda_2 \qquad (24)$$

or

$$\lambda_1 G_{kk} - \lambda_1 G_{kk}P_k \sum_{r\neq k}^{Q} \frac{G_{rk}}{(\sum_{j\neq r}^{Q} G_{rj}P_j + n)} = \frac{\lambda_2}{\prod_{r\neq k}^{Q} G_{ii}P_i}\prod_{i=1}^{Q}(\sum_{j\neq i}^{Q} G_{ij}P_j + n) \qquad (25)$$

Solving for P_k led to:

$$P_k = \left(\lambda_1 G_{ii} - \frac{\lambda_2}{\prod_{i\neq k}^{Q} G_{ii}P_i}\prod_{i=1}^{Q}(\sum_{j\neq i}^{Q} G_{ij}P_j + n)\right]\frac{1}{\lambda_1 G_{kk}\sum_{r\neq k}^{Q}\frac{G_{rk}}{(\sum_{j\neq r}^{Q} G_{rj}P_j + n)}}\Bigg) \qquad (26)$$

and further to

$$P_k(t+1) = \frac{1}{\sum_{r\neq k}^{Q}\frac{G_{rk}}{(\sum_{j\neq r}^{Q} G_{rj}P_j(t) + n)}} - \frac{\lambda_2}{\lambda_1 G_{kk}\prod_{i\neq k}^{Q} G_{ii}P_i(t)} \frac{\prod_{i=1}^{Q}(\sum_{j\neq i}^{Q} G_{ij}P_j(t) + n)}{\sum_{r\neq k}^{Q}\frac{G_{kr}}{(\sum_{j\neq k}^{Q} G_{rj}P_j(t) + n)}} \qquad (27)$$

Considering $\lambda_2 = 0$, then from (19) the problem was reduced to maximizing the throughput, and from (27) the throughput after constraining the transmitted power was one obtained. Without power constraints, Eqn. (27) rewritten as:

$$P_k(t+1) = \frac{1}{\sum_{r\neq k}^{Q}\frac{G_{rk}}{\sum_{j\neq r}^{Q} G_{rj}P_j(t) + n}}, t = 0,1 \dots, k = 1, \dots, Q \qquad (28)$$

$$P_{min} \leq P_k(t+1) \leq P_{max}$$

where G_{ij} is the channel gain between user j, and base stations i and n were additive noises. Without loss of generality, the user i was assumed to be assigned to base station i.

The problem in this case was minimized to:

$$J(P) = \begin{pmatrix} J_1(P_i) \\ J_2(P_i) \end{pmatrix} \qquad (29)$$

and with respect to $\boldsymbol{P_i}$ subject to possible constraints, had led to:

$$\tilde{J}(P_i) = \sum_{i=1}^{2} (w_1 J_1(P_i) + w_2 J_2(P_i)), i = 1, \dots, Q. \quad (30)$$

Here the weights $0 \leq w_1 \leq 1, w_2 = 1 - w_1$.

$$J_1(P_i) = (P_i(t) - P_{min})^2, i = 1, \dots, Q$$

$$J_2(P_i) = J_2\big(\Gamma_i(P_i)\big) = (\Gamma_i(t) - \log_2 \Gamma^{tg})^2, i = 1, \dots, Q$$

To find the minimum of the objective function in Eqn. (31),

$$J(P) = [\sum_{i=1}^{Q} \sum_{t=1}^{N} \gamma^{N-t} e_i^2(t)], t = 1, \dots, N \quad (31)$$

with respect to the power vector P, the error $e_i(t)$ was defined as:

$$e_i(t) = \lambda_1(P_i(t) - P_{\min}) + \lambda_2(\Gamma_i(t) + \log_2 \Gamma_i) \quad (32)$$

$$e_i(t) = \lambda_1(W_i^T X_i(t) - \mathrm{P}_{\min}) + \lambda_2 \left(\frac{G_{ii}(t) W_i^T X_i(t)}{I_i(t)} - \log_2 \Gamma_i \right). \quad (33)$$

Denoting

$$\alpha_t = \left[\lambda_1 + \lambda_2 \frac{G_{ii}(t)}{I_i(t)} \right] \quad (34)$$

And using it in Eqn. (33) $e_i(t)$ becomes:

$$e_i(t) = \alpha_t \mathrm{w}_i^T X_i(t) - \lambda_1 \mathrm{P}_{\min} - \lambda_2 \log_2 \Gamma_i. \quad (35)$$

From Eqns. (30) and (35), a necessary condition for the minimization is given as:

$$2 \sum_{t=1}^{N} \gamma^{N-t} e_i(t) \frac{\partial e_i(t)}{\partial \mathrm{w}} = 0 \quad (36)$$

From Eqn. (35)

$$\frac{\partial e_i(t)}{\partial \mathrm{w}} = \alpha_t X_i^T(t) (37)$$

By substituting Eqns. (35) and (37) into (36), we obtained

$$\sum_{t=1}^{N} \gamma^{N-t} e_i(t) \frac{\partial e_i(t)}{\partial \mathrm{w}} = \sum_{t=1}^{N} \gamma^{N-t} (\alpha_t \mathrm{w}_i^T X_i(t) - \lambda_1 \mathrm{P}_{\min} - \lambda_2 \log_2 \Gamma_i) \alpha_t X_i^T(t) = 0 \quad (38)$$

The minimization of the function in Eqn. (38) with respect to $\mathrm{P}_{\min}$ was then transformed into minimizing (38) with respect to the parameter vector w for the minimization of the transmitted power and the throughput (multi-objective).

3. Particle Swarm Optimization

Particle swarm Optimization (PSO) is a swarm Intelligence method for global optimization. It differs from other well-known Evolutionary Algorithms (EA). As in EA, a population of potential solutions was used to probe the search space, but no operators, inspired by evolution procedures, are applied on the population to generate new promising solutions. Instead, in PSO, each individual, named particle, of the population, called swarm, adjusts its trajectory toward its own previous best position, and toward the previous best position attained by any member of its topological neighbourhood. Thus, global sharing of information takes place and the particles profit from the discoveries and previous experience of all other companions during the search for promising regions of the landscape. In the single-objective minimization case, such regions posses lower function values than others. In the local variant of PSO, the neighbourhood of each particle in the swarm is restricted to a certain number of other particles but the movement rules for each particle are the same in the two variant.

Many popular optimization algorithms are deterministic, like the gradient-based algorithms. Compared with gradient-based algorithms, the PSO algorithm is a stochastic algorithm that does not need any gradient information. This allows the PSO algorithm to be used on many functions where the gradient algorithm is either unavailable or computationally obtained. In the past several years, PSO algorithm has been successfully applied in many research and application areas (Zielinski et al, 2007, Mathos et al, 2014). PSO is also attractive because there are fewer parameters to adjust (Meigin et al, 2016). It is demonstrated that PSO gets better results in a faster, cheaper way compared with many other methods.

3.1. Proposed PSO-based Algorithm for Power Control Problem

The PSO algorithm that was used to minimize a fitness function that takes into consideration all the objectives of the power control problem and finally PSO reaches a power vector that satisfies all these objectives to a great extent. In PSO-based algorithm, every particle in the swarm represent a power vector containing power values to be transmitted by all mobile units in order to be evaluated and enhanced by the algorithm. Note also that this method of representation of the power vector inherently satisfies the maximum power constraint as one always assigns the values of P_{max}.

In order to test the effectiveness of the proposed algorithm, the particles of the swarm was first initialized to totally random particles. Of course, this is not the real case, because in a real system the mobiles' power was updated from the values of the power in the last frame. After that, the PSO algorithm was applied with the proposed fitness function to these randomly initialized particles. The procedure of the proposed algorithm is as shown in Figure 2.

The PSO pseudo-code for the algorithm

For $i = 1$ to number of individuals
If $\mathrm{G}(\bar{x}_i) > G(\bar{P}_i)$ then do // G ( ) evaluates fitness
For $d = 1$ to Dimensions // P_{id} is best so far
$P_{id} = X_{id}$
Next *d*
End *do*
g = *i* // arbitrary
For *j* = indices of neighbors
If $\mathrm{G}(\bar{P}_{\mathrm{j}}) > G(\bar{P}_g)$ then $g = j$ // g is index of best performer in the neighborhood
Next *j*
For *d* = 1 to dimensions
$\mathrm{V}_{id}(\mathrm{t}) = \mathrm{V}_{id}(\mathrm{t}-1) + \varphi_1(\mathrm{P}_{id} - \mathrm{X}_{id}(\mathrm{t}-1) + \varphi_2\left(\mathrm{P}_{gd} - \mathrm{X}_{id}(\mathrm{t}-1)\right)$
$\mathrm{V}_{id} \epsilon (-\mathrm{V}_{max}, \mathrm{V}_{max})$
$\mathrm{V}_{id}(\mathrm{t}) = \mathrm{X}_{id}(\mathrm{t}-1) + \mathrm{V}_{id}(\mathrm{t})$
Next *d*
Next *i*

X_i is the position of particles *i*, V_i is the velocity of particles *i*, φ_1 is a random number that gives the size of step towards personal best, φ_2 is a random number that gives the size of the step towards global best (the best particle in the neighborhood) and G is the fitness function to be minimized.

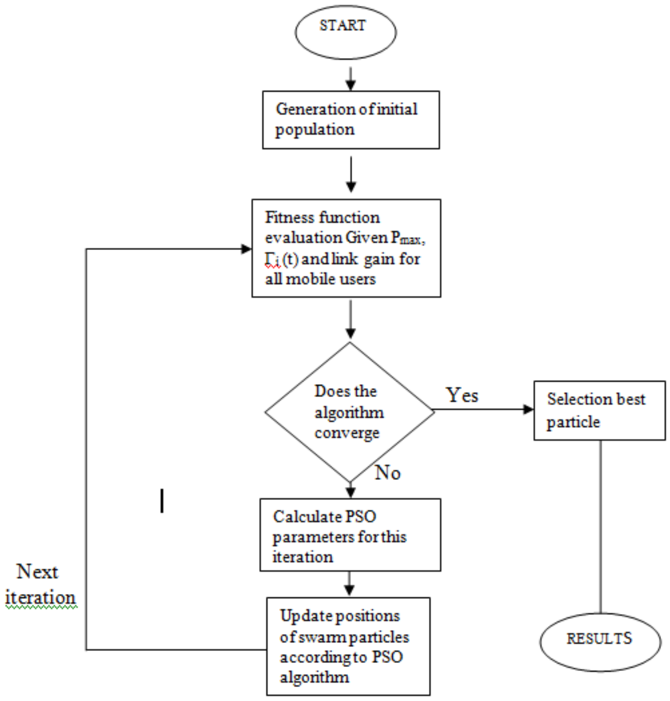


Figure 2: Proposed PSO-based algorithm for power control

4. Results and Discussions

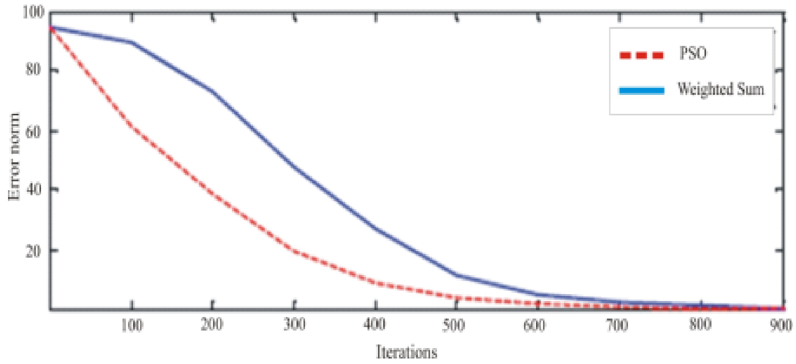
The simulation was done for four base stations uniformly distributed in an area of 4 km^2 containing 100 users. Mobile users were distributed uniformly over the cell space. As a result, the same equation was used to calculate the link gain of the mobile users. It has been assumed that updates were done on the positions of the mobile users and the fading conditions. The particles of the swarm were initialized to totally random number following the procedure described in the flow chart (Figure 2). The simulation was done several times while varying the number of users in the cell.

The PSO based power control algorithm fitness function used to minimize the power control problem were also used for weighted sum approach power control algorithm to minimize the same fitness function in order to compare their results and to see the effectiveness of the proposed algorithm. The optimum power vector is the solution of the distributed power control algorithm. The outage is the percentage of users that do not achieve the minimum tolerable CIR level.

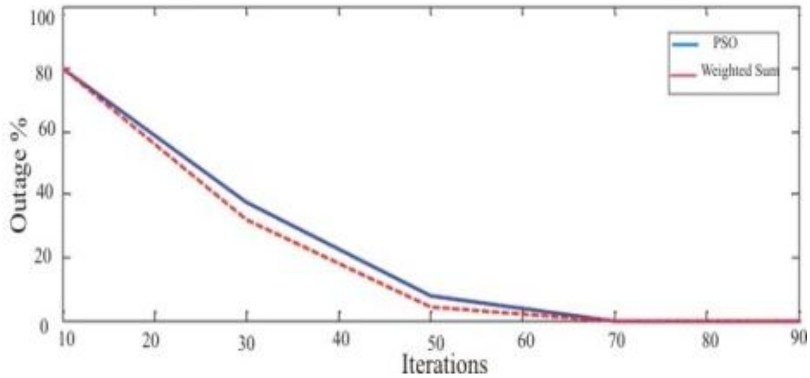
The transmitted power of all users in dB of PSO based power control algorithm for dynamic and static scenarios was considered. The results of each algorithm have been represented by the norm of the error and the outage percentage. The error is defined as the difference between actual transmitted power vector of the power control algorithm and the optimum power vector.

4.1. Transmitted Power and Carrier to Interference Ratio

In this case, for the purpose of comparison, the simulation was done for weighted sum approach and the PSO-based power control algorithm for dynamic and static scenario. Figure 3 (a) shows the error norm and (b) outage percentage for the static channel scenario, which indicates that the PSO-based power control converged faster than the weighted sum approach for static scenario. Figure 4 (a), (b), and (c) shows the comparisons between PSO and Weighted Sum Approach power control algorithms in terms of Error norm and the outage for the dynamic channel scenario as from table 1. As the iterations increased, the average value of error norm decreased because of the increase of the interference level between the users. Also, the average value of the transmitter power increased because the mobile units had to increase their transmitted power in order to overcome the increase in the interference level and to maintain an acceptable quality of service per user.

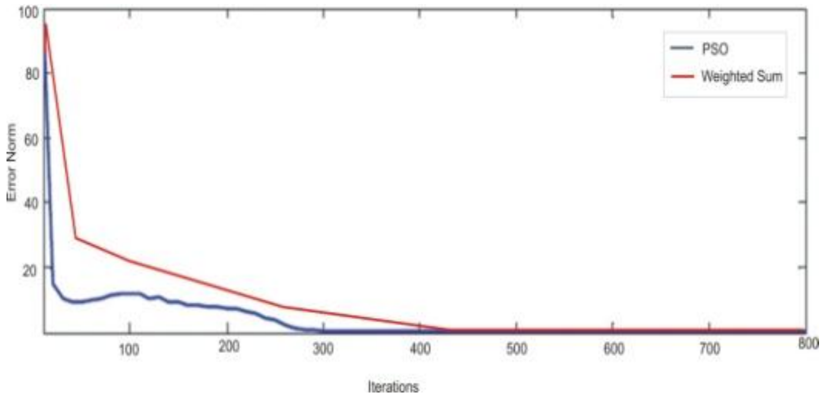


(a)

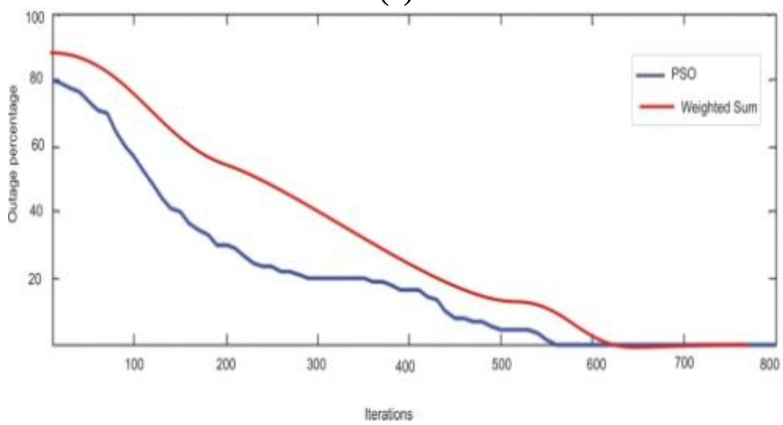


(b)

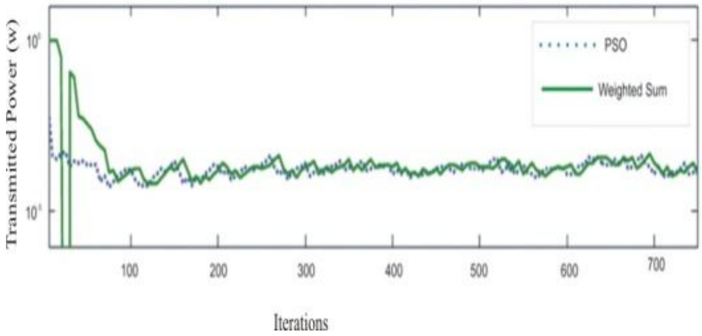
Figure 3: (a) Error norm and (b) the outage percentage for the static channel scenario



(a)



(b)



(c)

Fig. 4 (a) Error norm (b) The outage percentage and (c) Transmitted power for the dynamic channel scenario

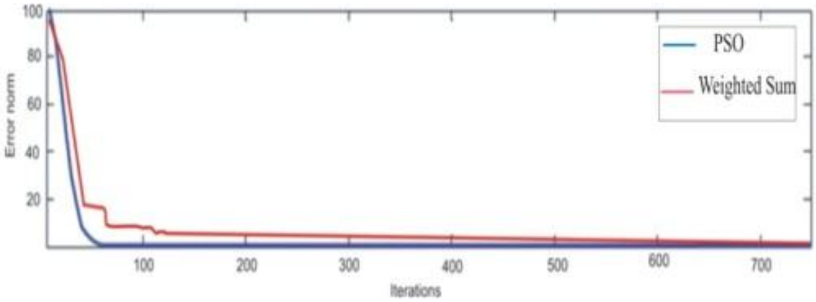
Table 1: Comparison of PSO-based power control with Weighted Sum Approach for minimization of the Transmitted Power and Carrier-to-Interference Ratio

	Weighted Sum Approach Distributed Power Control Algorithm			PSO-Based Distributed Power Control Algorithm		
Number of Users	Average CIR (dB)	Average Transmitted Power (w)	Outage Probability	Average CIR (dB)	Average Transmitted Power (w)	Outage Probability
5	7.000	0.273	0	4.000	0.183	0
10	5.001	0.371	0	5.003	0.221	0
15	6.005	0.381	0	4.004	0.232	0
20	6.000	0.496	0	5.000	0.291	0
30	7.002	0.652	0	6.001	0.521	0
40	5.001	0.998	0	4.000	0.999	0
55	7.005	0.865	0	5.000	0,764	0
65	6.000	0.976	0	4.001	0.866	0
70	6.004	0.754	0	7.005	0.692	0
80	5.000	0.976	0	4.000	0.944	0
90	7.002	0.988	0	6.004	0.922	0
100	5.000	0.999	0	4.000	0.998	0

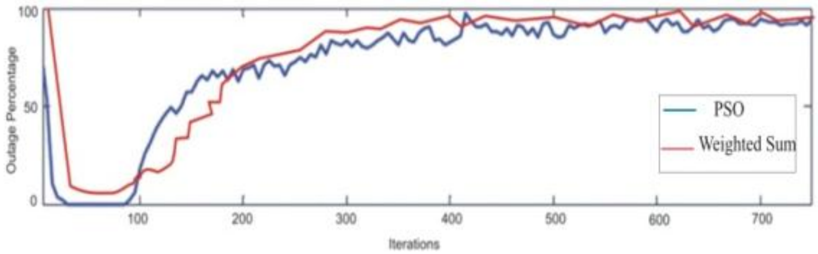
4.2. Transmitted Power and Throughput

Fig. 5 displays the error norm and the outage of the system using the PSO-based and the weighted Sum Approach distributed power control algorithm for the static scenario. It is clear that the power has converged at about iteration number 40. The outage is zero after iteration number 20 and then rose to about 70% at iteration number 100. Figure 6 shows the error norm, the outage percentage and the transmitted power for the dynamic channel scenario. The results of average transmitted power for the mobile units are presented in Figure 6. In respect of the average transmitting power for the mobile units, PSO algorithm converges with much smaller values of transmitted power to serve the same number of users. The resulting values of PSO algorithm are about 65% on average from those of weighted sum algorithm. This means that PSO algorithm is much better in searching the search space when the maximum number of iterations is reached.

Table 2 also shows the comparison between the PSO-based and the weighted sum approach distributed power control in terms of average carrier to interference ratio, the average transmitted power and the outage probability. The average received CIR was found to be slightly better for the weighted sum algorithm than those obtained by PSO algorithm. This was an expected result because the result of weighted sum algorithm used greater values for transmitted power and thus they probably will achieve better average received carrier-to-interference ratio (CIR). In spite of the fact that weighted sum results are better than PSO results, the results for both algorithms are very identical to each other. The resulting values of PSO algorithm are about 99% on average from those of weighted sum algorithm.

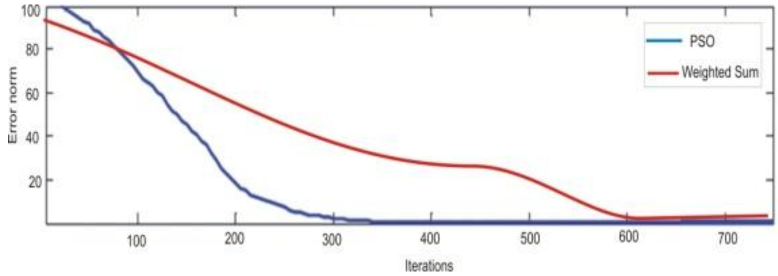


(a)

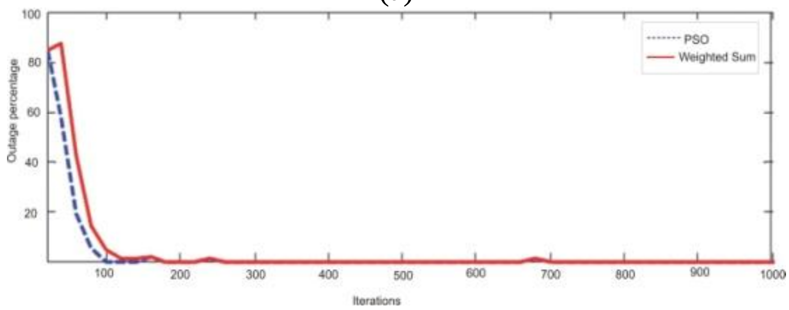


(b)

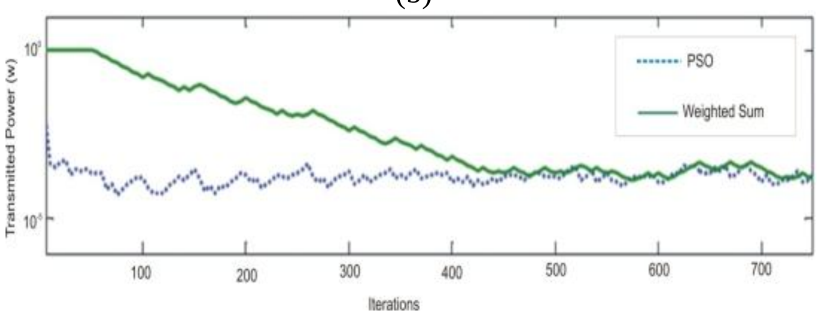
Fig. 5 (a) Error norm and (b) the outage percentage for the static channel scenario.



(a)



(b)



(c)

Fig. 6 (a) Error norm (b) The outage percentage and (c) Transmitted power for the dynamic channel scenario.

Table 2: Comparison of PSO-based power control and Weighted Sum approach for minimization of Transmitted Power and Throughput

	Weighted Sum Approach Distributed Power Control Algorithm			PSO-Based Distributed Power Control Algorithm		
Number of Users	Average CIR (dB)	Average Transmitted Power (w)	Outage Probability	Average CIR (dB)	Average Transmitted Power (w)	Outage Probability
5	7.002	0.283	0	4.000	0.193	0
10	5.001	0.371	0	5.001	0.241	0
15	6.000	0.381	0	4.000	0.236	0
20	6.005	0.496	0	5.003	0.293	0
30	7.002	0.662	0	6.000	0.551	0
40	5.000	0.998	0	4.004	0.999	0
55	7.000	0.875	0	5.000	0,766	0
65	6.003	0.976	0	4.001	0.876	0
70	6.004	0.784	0	7.000	0.695	0
80	5.003	0.976	0	4.000	0.944	0
90	7.004	0.998	0	6.003	0.922	0
100	5.000	0.999	0	4.000	0.998	0

5. Conclusion

In this paper, a new algorithm for the power control problem in wireless radio system is presented. It makes use of the powerful PSO-based method. The main advantages made in this approach are modifying the fitness function in order to handle the minimization of the near-far effect in a more effective way and applying the PSO algorithm to get a power vector that satisfies all the objectives of the power control in wireless radio system problem. The algorithm was modified to react to updated mobile users' positions and fading conditions in order to have the ability to be implemented in a real wireless radio system network. Experimental simulations proved the efficient performance of the proposed fitness function. These simulations also proved that the developed technique can produce results that outperform the results of trying to maximize the same fitness function using weighted sum approach. Also, the developed technique produced good results when it was tested while changing users' conditions. As a suggestion for future work, the hardware implementation of the proposed algorithm trying to implement it using DSP processors or FPGAs may be studied. Studying this implementation will give a decision if this algorithm can be really implemented in a wireless radio system standard or it will face some implementation problems.

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